Journal of Theoretical and Applied Information Technology
15th June 2017. Vol.95. No 11

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

AN EFFICIENT IMAGE COMPRESSION BASED ON MODIFIED HAAR WAVELET

[1]ABDULLAH MOHAMMED AWAD, [2]MUZHIR SHABAN AL-ANI

[1]University of Anbar, College of Computer Science and Information Technology, Department of Computer Science, Anbar, Iraq

[2]University of Human Development, College of Science and Technology, Department of Computer Science, Sulaimani, KRG, Iraq

E-mail: [1]am_awad2@yahoo.com, [2]muzhir.al-ani@uhd.edu.iq

ABSTRACT

Haar transform is one of the simplest and basic transformation from the multi-resolution spectrum. The attracting features obtained from Haar transform make it a potential candidate in modern applications, such as signal and image compression. The Haar wavelet transform provides mean values that compress the image so that it takes up much less storage space, and therefore transmits faster electronically and in progressive levels of detail. The main objective of this work is to modify the weighting factor in or der to study their effects on image compression. This paper tries to implement different scale of weighting factor and study their performance on the overall system of compression. Scale of weighting factor is used in order to prevent the pixel value from exceeding their limits. Different values of weighting factor are applied, these values are spans into two range to evaluate the implemented system. These values are implemented for various levels of 2D-DWT then we measure the performance via mean square error (MSE) and peak signal to noise ration (PSNR) in each step. The implemented system is simulated for wide range of weighting factors. The obtained results indicated that a good results can be achieved between a=1.6 to a=5.0.

Keywords: *2D-DWT, Image Compression, Discrete Wavelet Transform, Haar Transform; Weighting Factor.*

1. INTRODUCTION

Haar transform was proposed in 1910 by a Hungarian mathematician Alfred Haar which is one of the earliest transform functions proposed [1]. Haar transform uses Haar function for its basis, and it is an orthogonal rectangular pair [2]. Compared to the Fourier transform basis function which only differs in frequency, the Haar function varies in both scale and position, for its simplicity it is applied in a wide area of applications [3].

The main task in every kind of image processing is finding an efficient image representation that characterizes the significant image features in a compact form, on the other words how to represent images in a minimum number of values without significant reduction of characteristics [4]? Here, the 2D discrete wavelet transform (DWT) is one of the most important tools [5]. Conventionally, the 2D DWT is a separable construction, based on the 1D wavelet transformation which is independently applied to the rows and columns of an image [6]. Different wavelet families are implemented on image compression, such as Harr, Daubechies, Symlets, Coiflets, …etc [7]. These families concentrated on the variation in weighting factors [8]. The performance evaluation applied on DWT and other compression algorithms such as DCT, SVM, FFT also are studied and equipped wide applications [9],[10].

Many works are published in this field because of their wide range of applications. In this paper, we introduce an efficient algorithm of DWT whose underlying idea is simple but very effective and modified Haar wavelet. The proposed method is especially designed for Haar wavelet applied for image compression. The proposed approach concentrated on the modification of the weighting factor and their effects of the image performance. The evaluation process is concentrated on comparing the compressed image with the retrieved image.

Journal of Theoretical and Applied Information Technology
15th June 2017. Vol.95. No 11

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

2. RESEARCH OBJECTIVE

Given the importance of data and image compression leading to large number of papers have been published on this subject. The aim of this work was to study the compression of images using wavelet Transform. In addition to designing an efficient approach to study the Haar weighting factor and its impact on image compression and then study the retrieving of original images after the decompression process.

3. DISCRETE WAVELET TRANSFORM

The Discrete Wavelet Transform (DWT), which is based on sub-band coding is found to yield a fast computation of Wavelet Transform [11]. It is easy to implement and reduces the computation time and resources required [12]. The DWT is computed by successive low pass and high pass filtering of the discrete time-domain signal [13]. Two dimensional discrete wavelet transform (2D DWT) can be applied via its application on rows and columns separately [14]. In the first level of decomposition of 2D DWT, the image is separated into four parts. Each of them has a quarter size of the original image [15]. They are called approximation coefficients (Low Low or LL), horizontal (Low High or LH), vertical (High Low or HL) and detail coefficients (High High or HH) as shown in figure 1 [16]. Approximation coefficients obtained in the first level can be used for the next decomposition level, as shown in figure 2 [17].

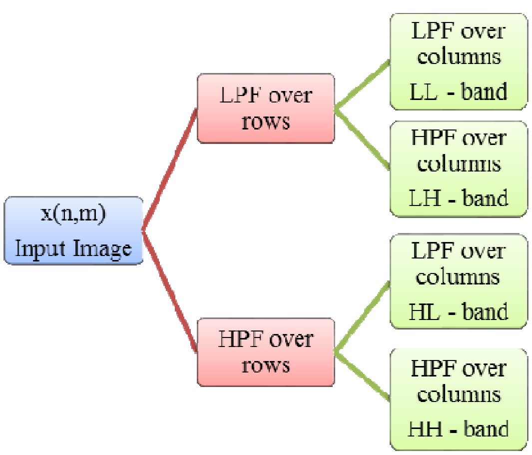

Figure1: Decomposition 2D-DWT

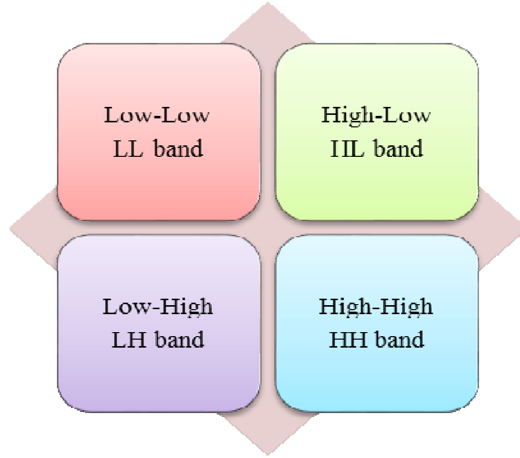

Figure 2: 2D-DWT bands

The Haar wavelet is a discrete simplest possible wavelet. Let us considered a signal [18],[19],[20],[21].

$x(n)$ $where\ n = 0 \ldots.., N-1$ ....(1)

$so\ \begin{pmatrix} X_n \\ X_{n+1} \end{pmatrix} = T \begin{pmatrix} X_{n+1} \\ X_{n+1} \end{pmatrix}$ ....(2)

Where the decompression matrix is

$T = (1/\sqrt{2})\begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix}$ ....(3)

Then the low pass filter values are

$X_0, X_2, \ldots. X_{N-2}$ ....(4)

And the high pass filter values are

$X_1, X_3, \ldots. X_{N-1}$ ....(5)

Let the 2D image is given by $x(n, m)$

Then the first level 2D decomposition is implemented by two steps.

The column wise decomposing is given by:

$$\begin{pmatrix} X1_{n,m} & X1_{n,m+1} \\ X1_{n+1,m} & X1_{n+1,m+1} \end{pmatrix} = T \begin{pmatrix} x_{n,m} & x_{n,m+1} \\ x_{n+1,m} & x_{n+1,m+1} \end{pmatrix} ..(6)$$

The row wise decomposing is given by:

$$\begin{pmatrix} X_{n,m} & X_{n,m+1} \\ X_{n-1,m} & X_{n+1,m+1} \end{pmatrix} = \begin{pmatrix} X1_{n,m} & X1_{n,m+1} \\ X1_{n+1,m} & X1_{n+1,m+1} \end{pmatrix} T^T ...(7)$$

The row/row sub matrix is generated as:

$$\begin{matrix} X_{0,0} & X_{0,2} & \ldots & X_{0,M-2} \\ X_{2,0} & X_{2,2} & \ldots & X_{2,M-2} \\ X_{N-2,0} & X_{N-2,2} & \ldots & X_{N-2,M-2} \end{matrix} ....(8)$$

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

4. RELATED WORK

Many papers are published related to the field of Haar wavelet, we will concentrated on the following:

Radomir S. et al. (2003) explained a brief survey of basic definitions of the Haar wavelet transform. Different generalizations of this transform are also presented. Sign version of the transform is shown. Efficient symbolic calculation of Haar spectrum is discussed. Some applications of Haar wavelet transform are also mentioned [22].

Ülo Lepik (2007) presented a survey on the use of the Haar wavelet method for solving nonlinear integral and differential equations is presented. This approach is applicable to different kinds of integral equations (Fredholm, Volterra, and integro-differential equations). Application to partial differential equations is exemplified by solving the sine-Gordon equation. All these problems are solved with the aid of collocation techniques [23].

Jonas Valantinas (2007) implemented a new original procedure for the evaluation of discrete Haar spectra for separate fragments (blocks) of a digital image is proposed. The procedure explores specific properties of Haar wavelets, refers to the assumption that Haar spectrum of the whole image is known, and is much faster than direct evaluation of Haar spectral coefficients for the respective image blocks [24].

Adnan Khashman et al. (2008) proposed that neural networks can be trained to establish the non-linear relationship between the image intensity and its compression ratios in search for an optimum ratio. This paper suggests that a neural network could be trained to recognize an optimum ratio for Haar wavelet compression of an image upon presenting the image to the network. Two neural networks receiving different input image sizes are developed in this work and a comparison between their performances in finding optimum Haar-based compression is presented [25].

Anuj Bhardwaj et al. (2009) studied the Modified Fast Haar Wavelet Transform (MFHWT) that is one of the algorithms which can reduce the calculation work in Haar Transform (HT) and Fast Haar Transform (FHT). This paper described the algorithm for image compression using MFHWT and showed better results than those obtained by using any other method on an average. This approach included a number of examples of different images to validate the utility and significance of algorithm's performance [26].

V. Ashok et al. (2010) proposed a Fast Haar wavelet for signal processing & image processing. In the proposed work, the analysis bank and synthesis bank of Haar wavelet is modified by using polyphase structure. Finally, the Fast Haar wavelet was designed and it satisfies alias free and perfect reconstruction condition. Computational time and computational complexity is reduced in Fast Haar wavelet transform [27].

Mohannad Abid Shehab Ahmed et al. (2011) an efficient image compression approaches can provide the best solutions to the recent growth of the data intensive and multimedia based applications. As presented in many papers the Haar matrix–based methods and wavelet analysis can be used in various areas of image processing such as edge detection, preserving, smoothing or filtering. In this paper, color image compression analysis and synthesis based on Haar and modified Haar is presented [28].

Sanjeev Kumar et al. (2012) covered some background of wavelet analysis, data compression and how wavelets have been and can be used for image compression. The paper examines a set of wavelet functions (wavelets) for implementation in a still image compression system and discusses important features of wavelet transform in compression of still images, including the extent to which the quality of image is degraded by the process of wavelet compression and decompression [29].

Dharmendra Kumar Gangwar et al. (2012) concentrated on achieving high compression ratios while retaining good details. Wavelet package is also support to save a computation, transmission, and storage costs etc. In this paper experimental analysis to determine compression ratio by discrete Haar wavelet transformation is done. The Haar wavelet transformation is composed of a sequence of low-pass and high-pass filters, known as a filter bank [30].

Sonam Malik et al. (2012) presented the comparison of the performance of discrete cosine transform, discrete wavelet transform and wavelets like Haar Wavelet and Daubechies Wavelet for

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

implementation in a still image compression system and to highlight the benefit of these transforms relating to today's methods. The performance of these transforms are compared in terms of Signal to noise ratio SNR, Mean squared error and Energy Retained etc. [31].

According to the above literature review, it can be mentioned that these works are concentrated on the types of wavelet transforms in addition to the accuracy of the implemented method or algorithm. The proposed approach try to test and examine different values of Haar weighting factor and their impact of the accuracy of compression and decompression process.

5. METHOGOLOGY

5.1 Proposed Modified Haar Wavelet Transform

As it is clear that Harr is an old transform, and it introduced in many applications. This paper is concentrated on the study of the modified Harr that deals with the effects of weighting factor on the obtained results. The implemented approach consists of the structure of forward 2D-DWT and inverse 2D-DWT as shown in figure 3 and figure 4 respectively. The implementation of Harr wavelet on images is a combination of low pass filter and high pass filter for both rows and columns. Comparing original image with the retrieved image via mean square error (MSE) and peak signal to noise ratio (PSNR). In this comparison, it is concentrated on the variation of the weighting factor that is an important part of Harr wavelet and it is affected both MSE and PSNR. Modified Harr wavelet procedure is illustrated in figure 5 in which you can select the adequate weighting factor values for forward and inverse wavelet functions according to the obtained results of MSE and PSNR.

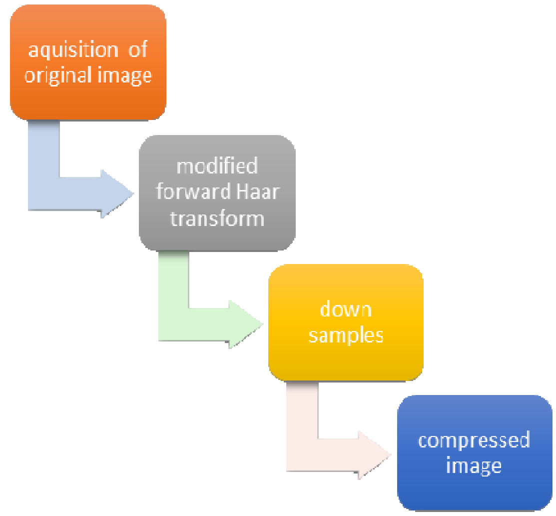

Figure 3: Forward 2D-DWT

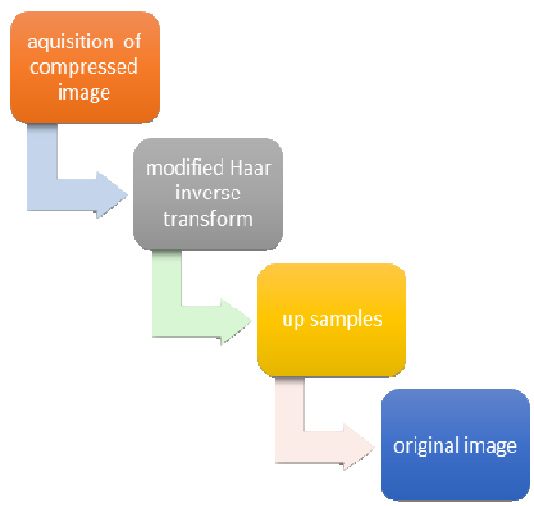

Figure 4: Inverse 2D-DWT

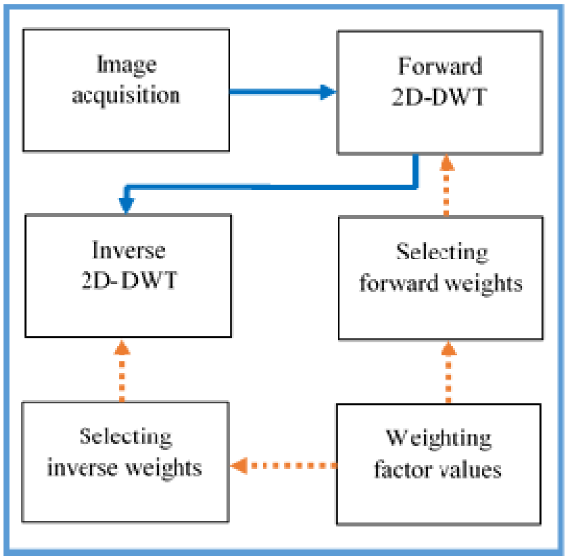

Figure 5: Modified Haar wavelet transform

5.2 Neural Network Implementation

Neural network fitting problem using a two-layer feed-forward network is applied in this work to compare the original image and the retrieved image. The direction procedure of this network starts from the input layer (original image), through the hidden layer (weights), and then to the output layer (retrieved image). In order to control the scope dimension of applying neural networks of this work, it is better to focus on the analyzing part of this tool. The simulation part of feed-forward neural network using Matlab is implemented via the following steps:

- First step (Network Architecture): in which the original image is assigned to the input layer and the retrieved image is assigned to the output layer. At the running of case, it generate the structure of the structure of the feed-forward neural network as shown in figure 6.
- Second step (Train Network): in which is implemented using back propagation neural network. This step is continue up to improve the validation of the system as shown in figure 7. The end of this step produces improve the system.
- Third step (Neural Network Iteration): in which it generate the performance of the tested system as shown in figure 8. The number of iteration is 804 with the required time 2 minutes and 23 seconds.
- Fourth step (Trained Network): in which occurs at the end of training, so the values of mean square error and regression are calculated. Lower value of mean square error is better and when the regression value reach to 1 this leads to close relationship as shown in figure 9.
- Fifth step (Evaluate Network): in which you can test the system for more data to check the network performance as shown in figure 10.
- Sixth step (Save Results): in which you can save all performance and structure in the form of Matlab as shown in figure 11.

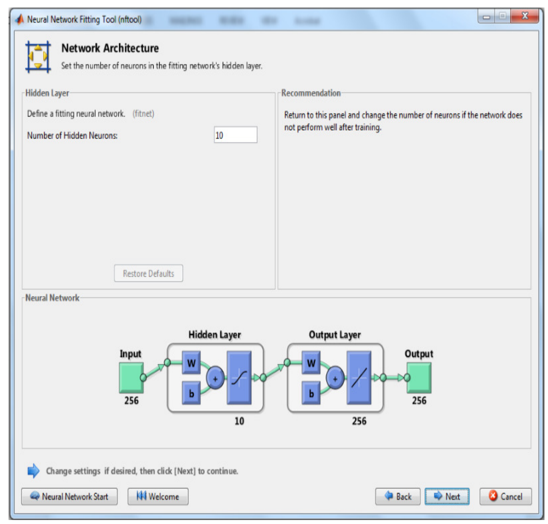

Figure 6: Network Architecture

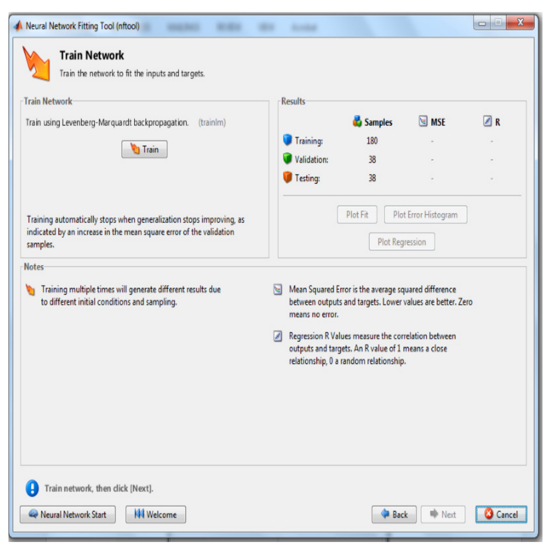

Figure 7: Train Network

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

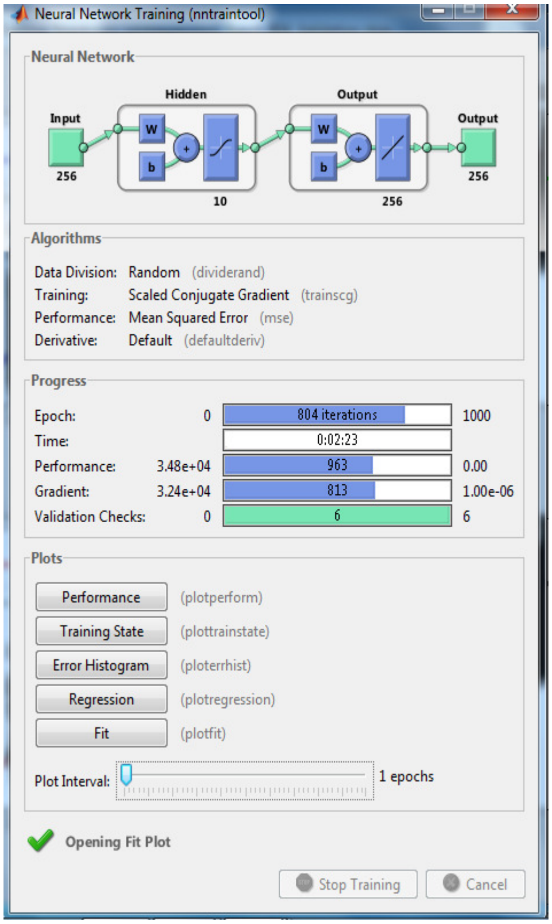

Figure 8: Neural Network Iteration

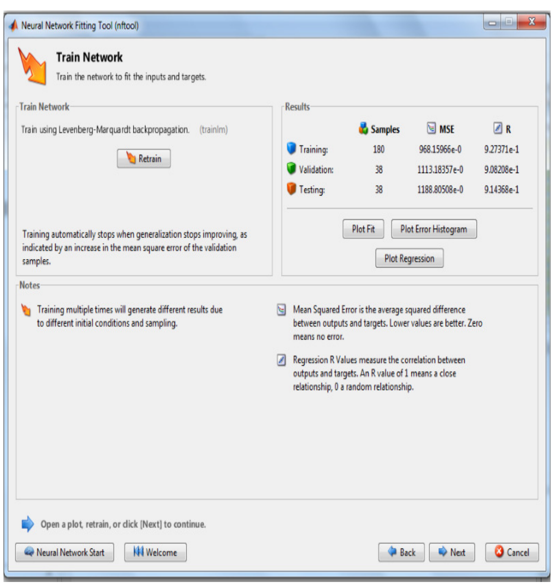

Figure 9: Trained Network

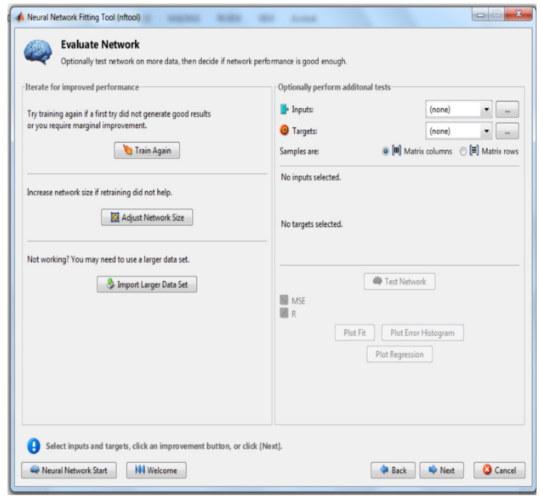

Figure 10: Evaluate Network

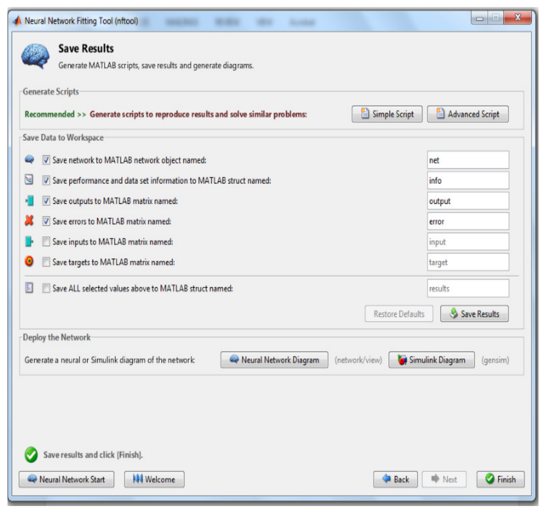

Figure 11: Save Results

6. RESULTS AND DISCUSION

6.1 Calculation of MSE and PSNR

Harr wavelet is implemented to achieve the system performance via applying different values of weighting factor. To reach an optimal solution we divided the weighting factor into two main intervals. In each increment of the interval we measure both mean square error and peak signal to noise ratio.

- First Interval: this interval vary with the low values interval $1 \leq a \leq 2$, with the increment of 0.1.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

- Second Interval: this interval vary with the high values interval $2 \leq a \leq 10$ with the increment of 1.

In this approach the simulated results of both MSE and PSNR are calculated for both two intervals. To evaluate and generalize these values, this approach is tested and evaluated for four levels (first level to forth level) of 2D-DWT.

Table 1, figure 12 and figure 13 show the distribution of MSE and PSNR for four levels of 2D-DWT according to the variation of weighting factor in the interval of $1 \leq a \leq 2$ with the increment of 0.1. MSE values are shown clearly in figure 5, these values expressed a large damping starting at the beginning of a=1.0 until reaching the value of a=1.7 and then approximately the MSE values reach the saturation values up to a=2.0. PSNR values are shown clearly in figure 13, these values are increased slowly with some dissonant values at the starting weighting factor values of a=1.0 and a=1.1 at exactly level four of 2D-DWT.

At this aspect it is clear that first interval of values $1 \leq a \leq 2$ leads to effective mean square error and peak signal to noise ratio.

Table 1: MSE For The First Interval

Weighs $1/(a)^{1/2}$	MSE			
	1st level	2nd level	3rd level	4th level
a=1.0	17380	10226	1253.9	0
a=1.1	13159	9552.7	1827.1	1.3584
a=1.2	9208.4	8171.2	2257.1	31.4463
a=1.3	6205.2	6657.8	2577.6	136.2529
a=1.4	3889.9	5404.9	2802.5	333.5586
a=1.5	2240.7	4396.6	2878.6	556.7803
a=1.6	1203.3	3300.2	2640.4	808.1836
a=1.7	585.928	2098.8	2192.2	1114.7
a=1.8	241.163	1106.7	1871.1	1410.3
a=1.9	76.9694	561.175	1717.0	1740.0
a=2.0	30.3699	359.957	1650.7	2181.0

Table 2: PSNR For The First Interval

Weighs $1/(a)^{1/2}$	PSNR			
	1st level	2nd level	3rd level	4th level
a=1.0	5.7304	8.0338	17.1481	inf
a=1.1	6.9385	8.3295	15.5132	46.8005
a=1.2	8.4890	9.0079	14.5953	33.1551
a=1.3	10.2033	9.8975	14.0186	26.7873
a=1.4	12.2315	10.8029	13.6553	22.8991
a=1.5	14.6270	11.6997	13.5389	20.6740
a=1.6	17.3270	12.9454	13.9140	19.0557
a=1.7	20.4524	14.9112	14.7221	17.6594
a=1.8	24.3077	17.6905	15.4098	16.6378
a=1.9	29.2676	20.6398	15.7831	15.7254
a=2.0	33.3064	22.5683	15.9542	14.7442

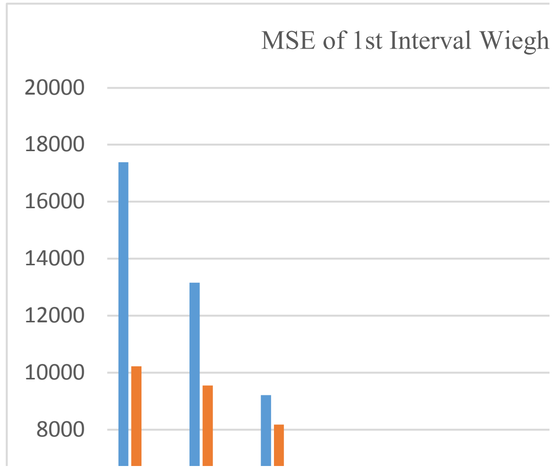

Figure 12: MSE Of First Interval Weighting Factor Of 2D-DWT

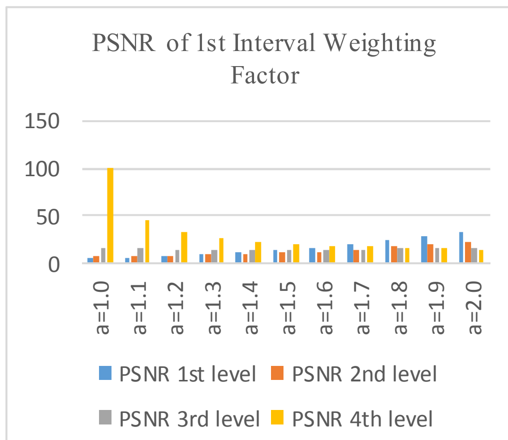

Figure 13: PSNR Of First Interval Weighting Factor Of 2D-DWT

Table 3, table4, figure 14 and figure 15 show the distribution of MSE and PSNR for four levels of 2D-DWT according to the variation of weighting factor in the interval of $2 \leq a \leq 10$ with the increment of 1.0. MSE values are shown clearly in figure 14, these values expressed a uniform distribution starting from the beginning of a=2.0 until reaching the value of a=4.0 with unregularly value of mentioned at the fourth level 2D-DWT when a=3.0. Then the rest of the values start decreasing up to the end of the distribution when a=10.0. On the other hand PSNR values are shown clearly in figure 15, these values are increased slowly and some significant values appeared at the fourth level of 2D-DWT.

As a contribution of the weighting factor values used with the 2D-DWT, it is clear the effective and efficient values appointed between a=1.6 to a=5.0. That means the effective scaling factor used with the 2D-DWT values will be in between 0.7906 to 0.4472.

Table 3: MSE for the second interval

Weighs $1/(a)^{1/2}$	MSE			
	1st level	2nd level	3rd level	4th level
a=2.0	30.3699	359.957	1650.7	2181.0
a=3.0	1156.3	2104.4	3836.3	6697.3
a=4.0	2080.2	2110.9	2121.3	2145.9
a=5.0	2617.4	1677.9	1074.7	689.4092
a=6.0	2928.5	1304.2	577.3921	253.8721
a=7.0	3126.3	1019.3	331.4844	107.6016
a=8.0	3256.4	810.298	203.1677	50.49710
a=10.0	3412.5	548.032	88.3513	14.9033

Table 4: PSNR for the second interval

Weighs $1/(a)^{1/2}$	PSNR			
	1st level	2nd level	3rd level	4th level
a=2.0	33.3064	22.5683	15.9542	14.7442
a=3.0	17.5001	14.8996	12.2917	9.8718
a=4.0	14.9498	14.8862	14.8647	14.8147
a=5.0	13.9520	15.8832	17.8181	19.7460
a=6.0	13.4644	16.9773	20.5161	24.0847
a=7.0	13.1805	18.0478	22.9262	27.8126
a=8.0	13.0034	19.0444	25.0523	31.0981
a=10.0	12.8001	20.7427	28.6687	36.3980

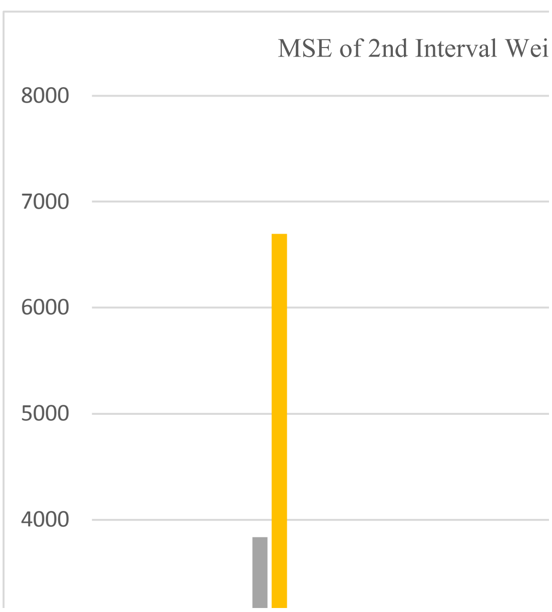

Figure 14: MSE Of First Interval Weighting Factor Of 2D-DWT

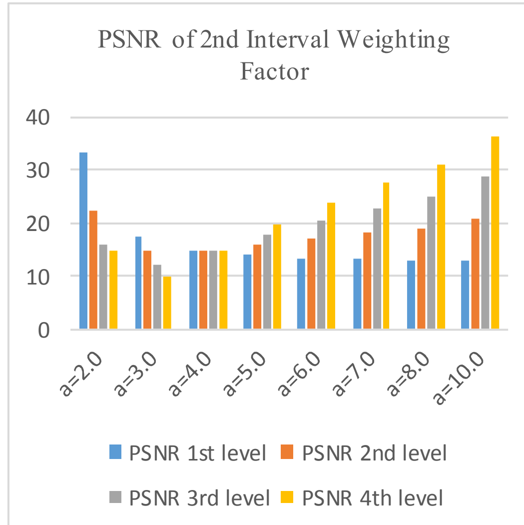

Figure 15: PSNR Of First Interval Weighting Factor Of 2D-DWT

6.2 Neural Network Training Results

Design and implementation of neural network are applied here to perform the system performance. Neural Network Training Performance is shown in figure 16 in which there four lines purple (train), green (validation), red (test) and dotted (best). This figure shows MSE according to the number of epoch up to 804 epochs. In this case the best performance is 1113.1836, this happen at epoch 7998.

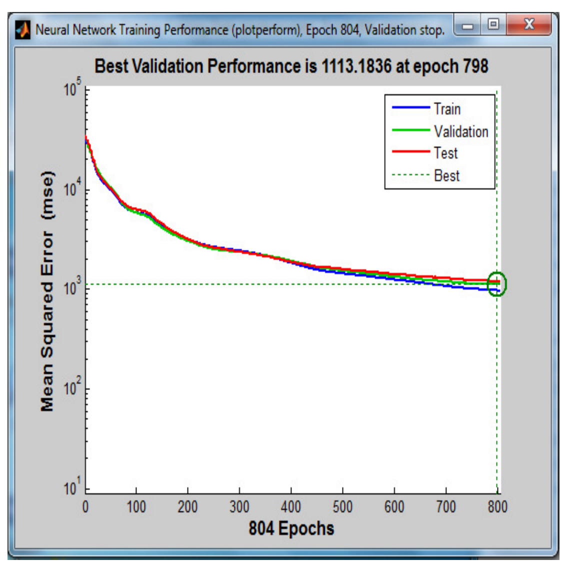

Figure 16: Neural Network Training Performance

Neural Network Training state is shown in figure 17, which divided into two parts: the first part measure the relation between gradient and number of epochs and the second part measure the relation between failed values and the number of epochs. In this case the minimum gradient is 813.3777 mentioned at epoch 804 in which the validation check is equal to 6.

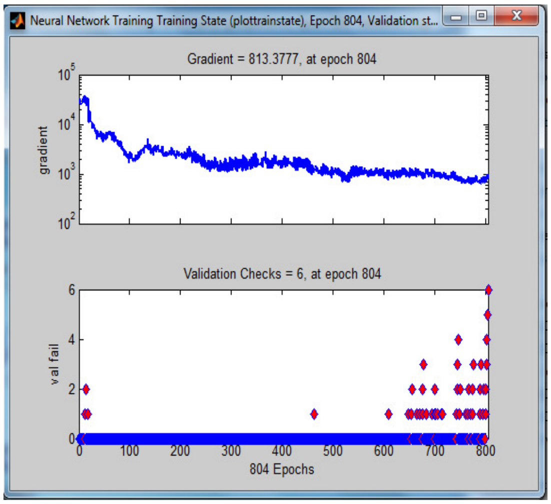

Figure 17: Neural Network Training State

Error histogram is shown in figure 18, in which illustrated the relation between instance and the Error. Four colors are shown these relations: blue (training), green (validation), red (test) and the orange line represents zero error.

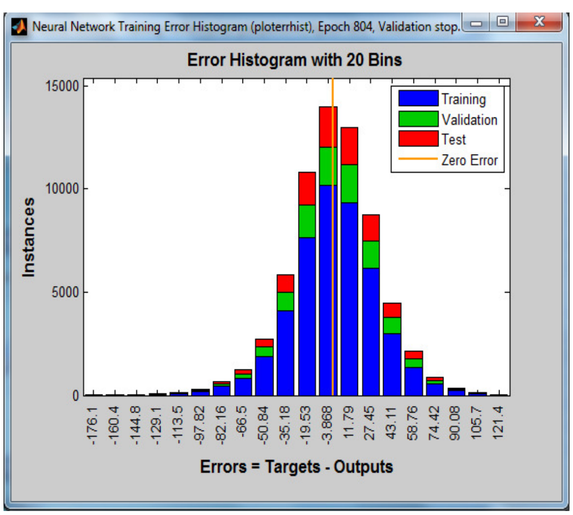

Figure 18: Error Histogram

Neural network training regression that shows the relation between output and target as shown in figure 19. This case demonstrates four parts: training (R=0.92737), validation (R=0.90821), test (R=0.91437) and all (R=0.92313).

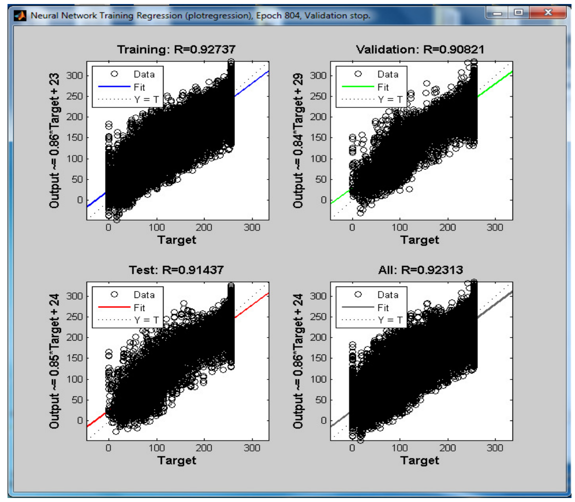

Figure 19: Neural Network Training Regression

Existing many wavelet families and each of these families have their benefits and limitations. According to the obtained results, it is clear that these results indicated a powerful characteristics during controlling and adapting of the weighting factor values. So by sensitive choosing the weighting factor via applying this approach you can get a suitable valve for your application.

7. CONCLUSIONS

Image compression form substantial problems in many engineering and biomedical applications. This paper is devoted to the study of the multi-resolution approach to this problem employing the modified Haar wavelet transform. In this paper, the computation algorithm of the Haar transform for images is proposed to study the variation of weighting factor. This study is concentrated on the variation in the values of weighting factor and how to select the suitable value. The weighting factor values are divided into two intervals; first interval is from 1 to 2 with the increment of 0.1 and the second interval is from 2 to 10 with the increment of 1. MSE and PSNR are measured in each increment to study the image performance. The obtained results indicated that the weighting factors of the values from 1.6 to 5 give a good performance that achieve relative image characteristics. So Harr 2D-DWT can be used to minimize the image size according to level number without significant losing of the resolution, within the limit of mentioned weighting factors. As a specific conclusion of the obtained results, we can

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

say that there is significant fluctuation of MSE and PSNR appeared at low and high values of the weighting factor, but there is unnoticed fluctuation of MSE and PSNR appeared in the mid rang of the weighting factor values.

Recently image compression plays an important role in our life for their wide applications in various fields. Internet of Things (IoT) is the future trend of the world and it companied and transfer a huge amount of data (text, audio, image and video) each minute. So the future trends is concentrated on the efficient, intelligent and adaptive approach to perform the compression. The selection of the efficient approach to be applied on a certain application it is a big challenge to be explained and studied for the future.

REFRENCES:

[1] R.S. Stanković and B.J. Falkowski. "The Haar wavelet transform: its status and achievements". Computers and Electrical Engineering, Vol.29, No.1, pp.25-44, January 2003.

[2] C. L. Chang and B. Girod, Direction-adaptive discrete wavelet transform for image compression, IEEE Trans. Image Process. 16(5) (2007), 1289–1302.

[3] W. Ding, F. Wu, X. Wu, S. Li, and H. Li, Adaptive directional lifting-based wavelet transform for image coding, IEEE Trans. Image Process. 16(2) (2007), 416–427.

[4] J. P. Antoine, D. Rosca, and P. Vandergheynst. Wavelet transform on manifolds: Old and new approaches. Applied and Computational Harmonic Analysis, 28:189 – 202, 2010.

[5] J. Krommweh. Tetrolet transform: A new adaptive Haar wavelet algorithm for sparse image representation. Journal of Visual Communication and Image Representation, 21:364–374, 2010.

[6] G. Plonka. The easy path wavelet transform: A new adaptive wavelet transform for sparse representation of two-dimensional data. Multiscale Modeling and Simulation, 7:1474–1496, 2009.

[7] Deepa T and Girisha H," Image compression using Hybrid wavelet Transform and their Performance Comparison", International Journal of Modern Engineering Research, Vol. 4, Issue. 6, June, 2014. [6] G.

[8] Buela Divya, M.Krupa Swaroopa Rani, "Implementation of Image Compression Using Hybrid DWT- DCT Algorithms", International journal of modern trends in engineering and research, Volume 02, Issue 07, 2015.

[9] Hussein M. Magboub and Mahmoud A. Osman, "Performance Evaluation of Discrete Wavelet Transform Based on Image Compression Technique on Both CPU and GPU", International Conference on Innovations in Engineering and Technology, Dec. 25-26, 2013

[10] Navpreet Saroya, Prabhpreet Kaur, "Analysis of image compression algorithm using DCT and DWT transforms", International Journal of Advanced Research in Computer Science and Software Engineering, vol 4, issue 2, February 2014

[11] Eckley, I. and Nason, G. (2011). Ls2w: implementing the locally stationary 2d wavelet process approach in r. Journal of Statistical Software, 43(3):1- 23.

[12] V. Galiano, O. López, M.P. Malumbres, H. Migallón, "Parallel strategies for 2D Discrete Wavelet Transform in shared memory systems and GPUs", Springer Science Business Media, LLC 2012.

[13] Rajesh K. Yadav, S.P. Gangwar and Harsh V. Singh," Study and analysis of wavelet based image compression techniques", International Journal of Engineering, Science and Technology vol. 4, no. 1, 2012

[14] Iwahashi, M., & Kiya, H. (2009). Non Separable 2D Factorization of Separable 2D DWT for Lossless Image Coding". IEEE Proc. International Conference Image Processing (ICIP), 17-20.

[15] Muzhir Shaban Al-Ani and Abdulrahman Dira Khalaf , "Image Information Retrieval Using Wavelet and Curvelet Transform", International Journal of Soft Computing and Engineering (IJSCE) ISSN: 2231-2307, Volume-3, Issue-1, March 2013

[16] Muzhir Shaban Al-Ani and Talal Ali Hammouri , "An Efficient Wavelet Mask Selection Approach for Image Compression", International Conference of Sciences of Electronics, Technologies of Information and Telecommunications, SETIT 2011, 26-29 October 2011, Tunisia.

[17] Muzhir Shaban Al-Ani & Alaa Sulaiman Al-waisy, "Face Recognition Approach Based on Wavelet – Curvelet Technique", Signal & Image Processing: An International Journal (SIPIJ) Vol.3, No.2, April 2012.

[18] A. Alice Blessie, J. Nalini and S.C.Ramesh, 2011, ―Image Compression Using Wavelet Transform Based on the Lifting Scheme and its Implementation‖ IJCSI International Journal of Computer Science Issues, Vol. 8-No. 1.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[19] Ms. Yamini S.Bute, Prof. R.W. Jasutkar, 2012, ―Implementation of Discrete Wavelet Transform Processor For Image Compression‖ International Journal of Computer Science and Network (IJCSN), Vol.1.

[20] Radomir S. Stankovic, Bogdan J. Falkowski, 2003, ―The Haar wavelet transform: its status and achievements‖ Computers and Electrical Engineering, 25–44

[21] P. Raviraj and M.Y. Sanavullah, 2007, ―The Modified 2D-Haar Wavelet Transformation in Image Compression‖. Middle-East Journal of Scientific Research, 2 (2): 73-78.

[22] Radomir S. Stankovic , Bogdan J. Falkowski, "The Haar wavelet transform: its status and achievements:, Computers and Electrical Engineering 29 (2003) 25–44.

[23] Ülo Lepik, "Application of the Haar wavelet transform to solving integral and differential equations", Proc. Estonian Acad. Sci. Phys. Math., 2007, 56, 1, 28–46.

[24] Jonas Valantinas, "On the Application of Harr Wavelets to Locally Progressive Encoding of Grey Level Images", Information Technology and Control, 2007, Vol.36, No.2.

[25] Adnan Khashman, Kamil Dimliler, "Image Compression using Neural Networks and Haar Wavelet", WSEAS TRANSACTIONS on SIGNAL PROCESSING, Issue 5, Volume 4, May 2008.

[26] Anuj Bhardwaj and Rashid Ali, "Image Compression Using Modified Fast Haar Wavelet Transform", World Applied Sciences Journal 7 (5): 647-653, 2009.

[27] V.Ashok T.Balakumaran C.Gowrishankar, The Fast Haar Wavelet Transform for Signal & Image Processing, (IJCSIS) International Journal of Computer Science and Information Security, Vol. 7, No. 1, 2010.

[28] Mohannad Abid Shehab Ahmed, Haithem Abd Al-Raheem Taha, Musab Tahseen Salah Aldeen, "Image Compression using Haar and Modified Haar Wavelet Transform", Tikrit Journal of Eng. Sciences/Vol.18/No.2/June 2011, (88-101).

[29] Sanjeev Kumar, Varun Sood, "Quality Assessment of Colour Image Compression using Haar Wavelet Transform", International Journal of Engineering Trends and Technology- Volume3Issue3- 2012.

[30] Dharmendra Kumar Gangwar, "Compression and Development Analysis on an Image Using Harr Wavelet Transformation", International Journal of Advanced Technology & Engineering Research (IJATER), VOLUME 2, ISSUE 3, MAY 2012.

[31] Sonam Malik and Vikram Verma, Comparative analysis of DCT, Haar and Daubechies Wavelet for Image Compression, International Journal of Applied Engineering Research, ISSN 0973-4562 Vol.7 No.11 (2012).